Expanding Our Estimation Tool Set: Formalizing Analogy Based Cost Estimation

Jairus Hihn
Alex Lumnah
Jet Propulsion Laboratory, California Institute of Technology

October 18-20, 2017

CSSE Systems Software Cost Modeling Forum

First Things First - The Team

- JPL/California Institute of Technology
  - Dr. Jairus Hihn
  - Elinor Huntington
  - Alex Lumnah
  - Michael Saing
  - Tom Youmans
- NASA Strategic Investment Division
  - James Johnson
- North Carolina State University (Original Research Team)
  - Dr. Tim Menzies
  - George Mathew

Contact:

Dr. Jairus Hihn, jairus.m.hihn@jpl.nasa.gov
James K. Johnson, james.k.johnson@nasa.gov

Some Stories….

Isn't software maintenance free? It was free at the university research programs!

- Program Office Manager

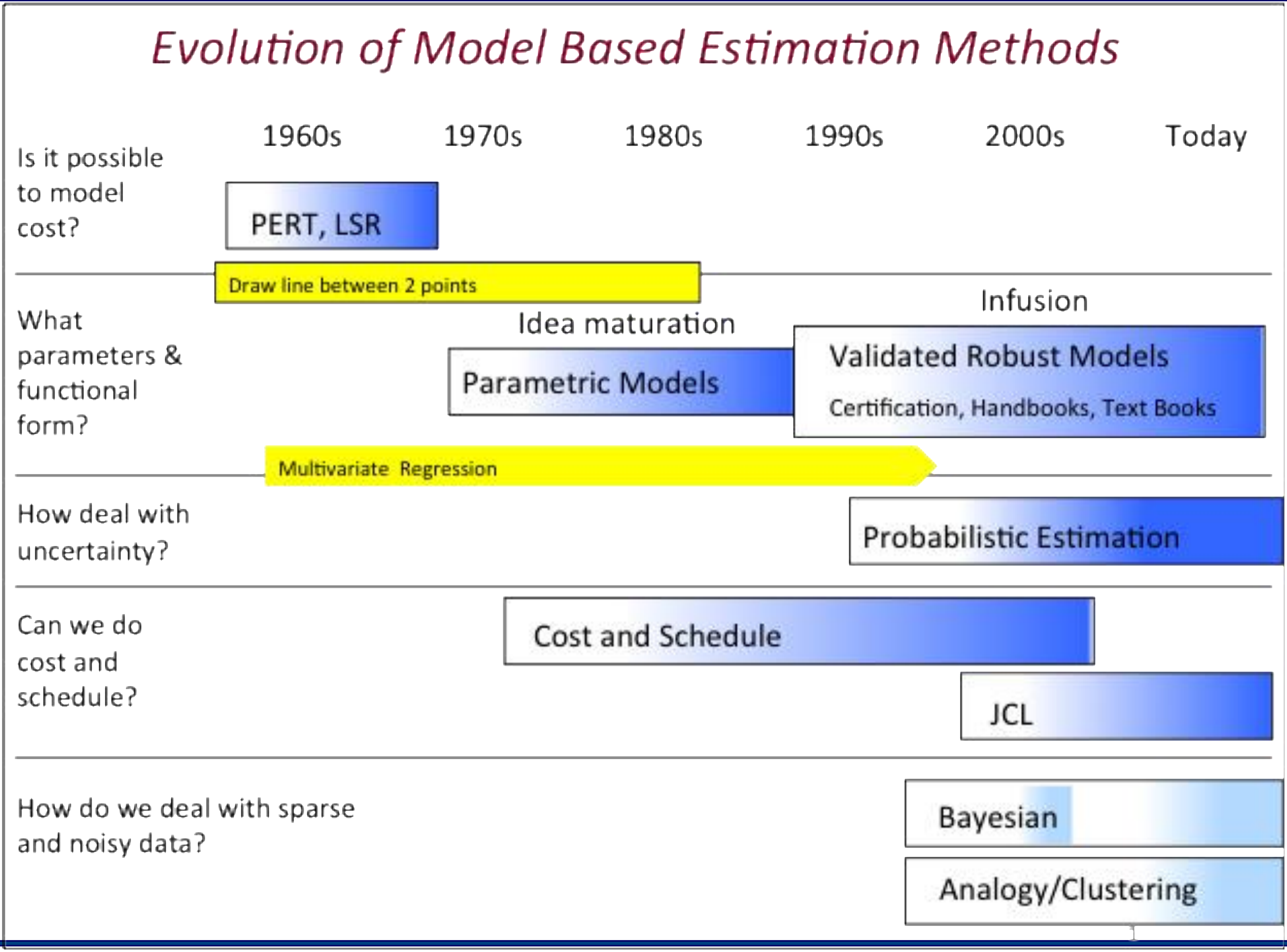
But we are just cloning the last mission so flight software budget is basically ZERO, right! (Oh and all the instruments/sensors have been changed)

- A Different Program Office Manager

Why explore alternative modeling methods?

- For most of our history the cost community has relied upon regression based modeling methods
- Sometimes regression breaks down
  - Regression methods have the underlying assumption of clean and complete data with large sample sizes
- Guess what - Most cost data suffers from sparseness, noise, and small sample sizes
- The point is we need more tools in our toolkit

Formal Analogy and Bayesian Models are a Natural Next Step in the Evolution Cost Modeling and Analysis



What We Learned from Methodology

- There are a variety of models whose performance are hard to distinguish (given currently available data) but some models are better than others
- If one has sufficient data to run a parametric model such as COCOMO then the best model has repeatedly been found to ne the parametric model
- When insufficient information exists then a model using only system parameters can be used to estimate software costs with ‘acceptable’ reduction in accuracy. The main weakness is the possibility of occasional very large estimation errors which the parametric model does not exhibit.
- A major strength of the nearest neighbor and clustering methods is the ability to work with a combination of symbolic and numerical data
- While a nearest neighbor model performs as well or better as clustering based on MMRE, clustering handles outliers better and provides a structured model that supports cost analysis and not just prediction

"ASCoT" Key Analysis Components

Analogy

Cluster Analysis

- Clustering
- Development Effort Estimate

Knn Analysis

- Nearest Neighbor
- Development Effort and SLOC Estimate

Regression Analysis

- Linear Regression
- Development Cost Estimate

COCOMO II

- Verified Reproduction
- Cost/Effort

- Cluster & Regression Analysis components listed rely on high level Mission Descriptors such as # of Instruments and Mission Type
- COCOMO II is a reproduction and uses traditional inputs

We Are Estimating With minimum Inputs

Cluster and KNN algorithms use

- Spacecraft Type
- Destination
- Number of Instruments
- Number of Deployables
- Software Inheritance Categories
- Mission Size ($) Categories

No SLOC

Regression Model uses

- Spacecraft Development Costs
- Number of Instruments

Improved Input Parameters

- Original Mission-Type parameter combined type of Mission Type with Destination

Mission Type	Values	Description	Example
	Orbiter	A Robotic spacecraft that orbits or it's target body. Also includes flyby spacecraft.	Aqua, New Horizons
	Observatory	Observatories are space based telescopes that support space based astronomy across a wide set of frequencies. They can be earth trailing or at the various LaGrange points created by the gravity fields of the earth, sun and moon.	Kepler
	Lander	A robotic spacecraft that does its science in-situ or from the surface of a solar system body. It does not move from its original location.	Phoenix
	Rover	A robotic spacecraft that does its science in-situ or from the surface of a solar system body and has the ability to move on the surface. To date all rovers have wheels but in the future they may crawl, walk or hop.	MSL
Destination	**Values**	**Description**	**Example**
	Earth	Missions that are in an Earth orbit.	OCO
	Inner Planetary	Missions that target planets within the asteroid belt. Also includes missions that are Heliocentric, Earth leading or trailing, at the Earth-Sun-Moon LaGrange points, and lunar mission.	Maven
	Asteroid/Comet	Missions that target asteroids or comets. As these may typically require more complex, or different, trajectories than inner planetary missions.	Dawn
	Outer Planetary	Outer Planetary missions are missions that travel beyond the asteroid belt.	JUNO

Data Summary – Key Metrics

- Total of 51 missions with data
  - 47 can be used in at least 1 of the estimation models

- Missions by Destination
  - Earth – 23
  - Asteroids/Comets – 7
  - Inner Planets– 17
  - Outer Planets – 4

Data Summary – Key Metrics

- Effort, Lines of Code and Productivity by Destination

Destination	# of Records	Effort (Months)		Logical Delievered LOC	
		Median	S.D.	Median	S.D.
Astreroids/Comet	7	546	373	143,000	35,189
Earth	23	499	466	62,000	39,986
Inner	17	664	435	122,000	133,765
Outer	4	620	411	54,000	21,633

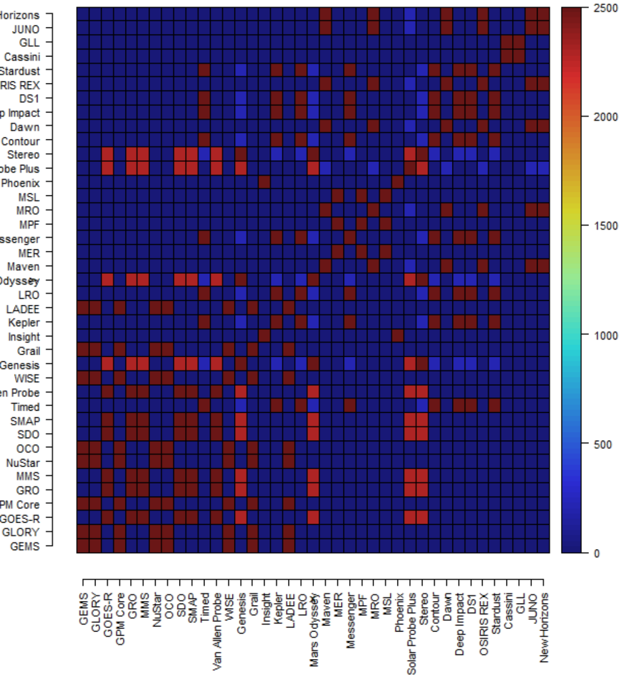
- Number of Deployable and Instruments by Destination

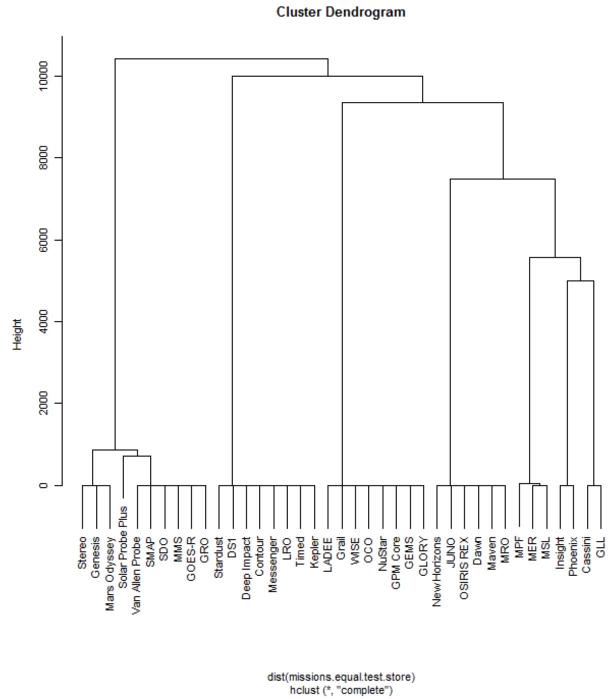
Destination	Instrument		Deployable	
	Median	Range	Median	Range
Astreroids/Comet	3	2-5	1	0-3
Earth	3	1-10	2	0-8
Inner	4	3-10	2	0-10
Outer	10	7-12	3	0-8

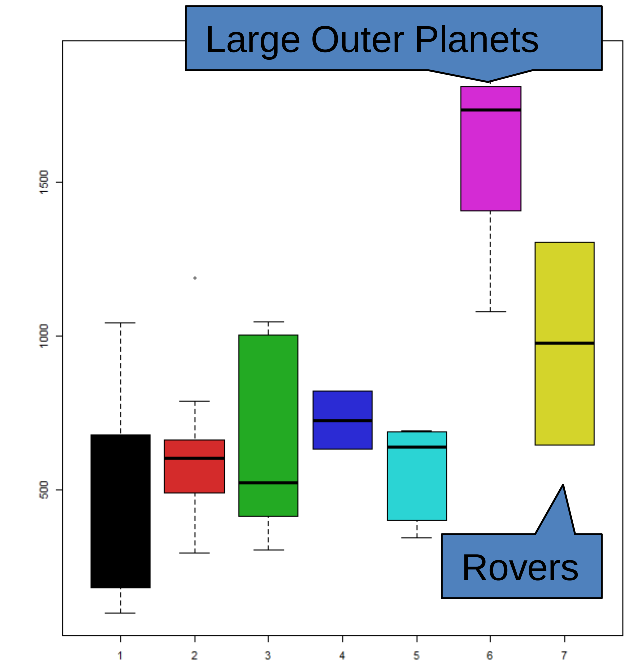
Clustering Algorithms Evaluated

- Conducted extensive analysis to verify this was indeed the best method
  - Spectral Clustering
  - K-Means
  - Hierarchical Clustering
  - PCA- Principle Components

- The methods were examined for
  - cluster membership stability
  - minimum within-cluster range
  - Effort estimation error based on leave-one-out MRE





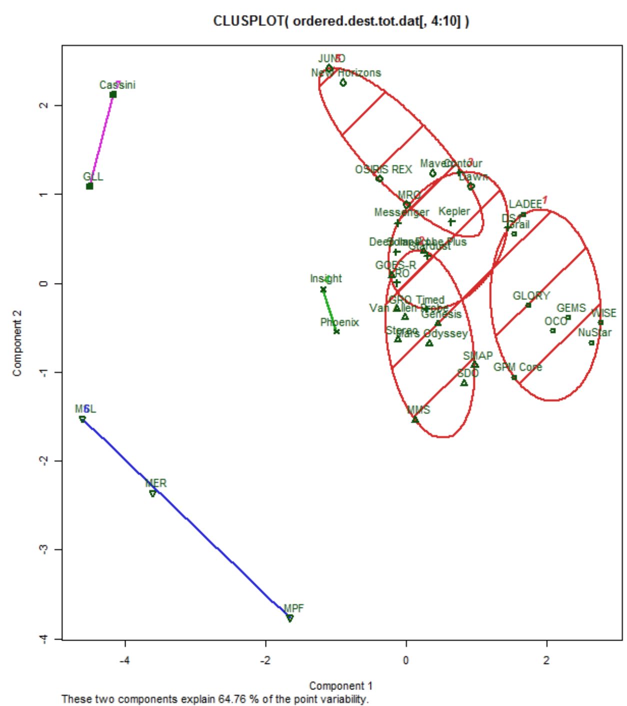


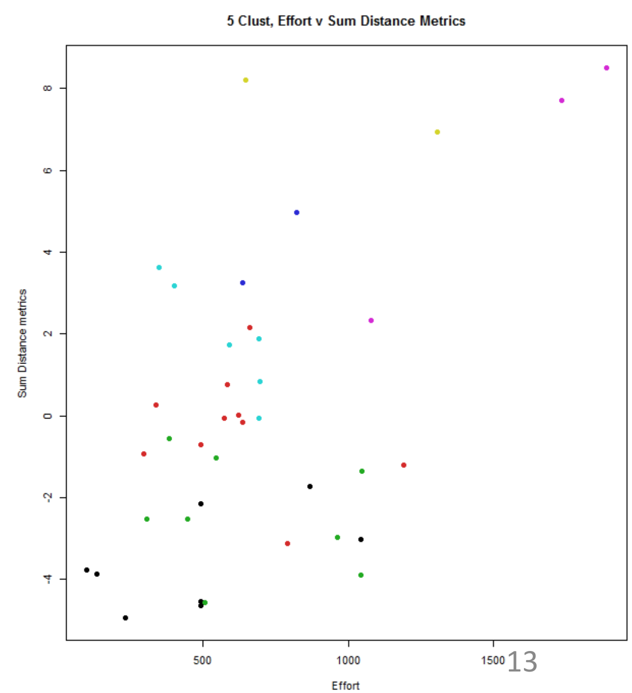
Rm: HST (Hubble, 1830), Near (48)

Mission	Effort	Dest	Type	Grp
GEMS	100	Earth	Orbiter	1
GLORY	133	Earth	Orbiter	1
GPM Core	1043	Earth	Orbiter	1
NuStar	493	Earth	Orbiter	1
OCO	492	Earth	Orbiter	1
WISE	233	Earth	Orbiter	1
Grail	868	Inner	Orbiter	1
LADEE	492	Inner	Orbiter	1
GOES-R	584	Earth	Orbiter	2
GRO	492	Earth	Orbiter	2
MMS	662	Earth	Orbiter	2
SDO	1190	Earth	Orbiter	2
SMAP	789	Earth	Orbiter	2
Van Allen Probe	295.6	Earth	Orbiter	2
Genesis	637	Inner	Orbiter	2
Mars Odyssey	336	Inner	Orbiter	2
Solar Probe Plus	621	Inner	Orbiter	2
Stereo	571.6	Inner	Orbiter	2
Timed	504	Earth	Orbiter	3
Kepler	446	Inner	Orbiter	3

Mission	Effort	Dest	Type	Grp
LRO	964	Inner	Orbiter	3
Messenger	384.4	Inner	Orbiter	3
Contour	307	Ast/Com	Orbiter	3
Deep Impact	1047.9	Ast/Com	Orbiter	3
DS1	1042.8	Ast/Com	Orbiter	3
Stardust	546	Ast/Com	Orbiter	3
Insight	822	Inner	Lander	4
Phoenix	634	Inner	Lander	4
Maven	694	Inner	Orbiter	5
MRO	691	Inner	Orbiter	5
Dawn	691.43	Ast/Com	Orbiter	5
OSIRIS REX	401.01	Ast/Com	Orbiter	5
JUNO	346	Outer	Orbiter	5
New Horizons	591.1	Outer	Orbiter	5
MER	1735.4	Inner	Rover	6
MPF	1080	Inner	Rover	6
MSL	1888	Inner	Rover	6
Cassini	1307	Outer	Orbiter	7
GLL	648	Outer	Orbiter	7

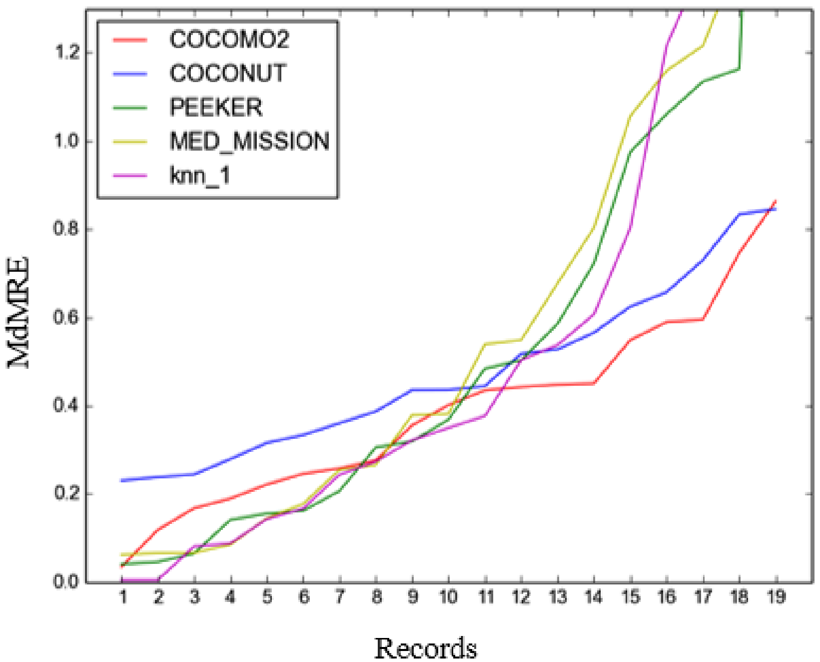
This!





Comparing Model Performance

- To compare models we use MRE metrics from leave one out validation
- COCOMO II out of the box performs well against parametric and non-parametric models
- Even performs well against local calibration
- If you have enough information run a parametric model !!

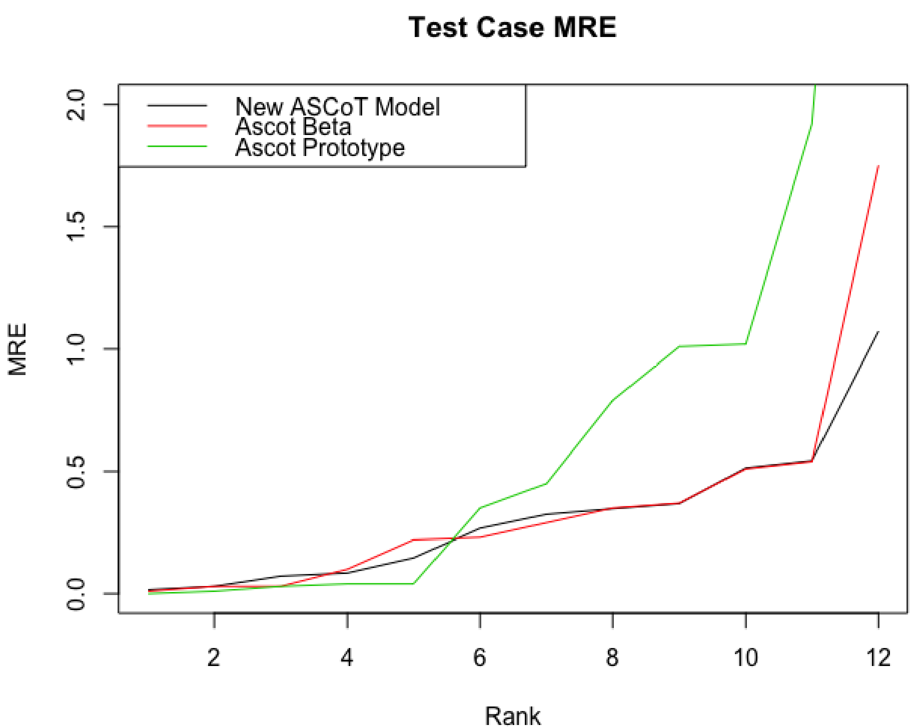


Estimation Model	Median MRE (MMRE)	25^{th} Percentile	75^{th} Percentile
Knn1 (Nearest Neighbor)	32%	14%	80%
PEEKING2 (Spectral Clustering)	32%	16%	97%
COCOMO2	36%	22%	55%
Mission Type Summary Table	38%	14%	106%
COCONUT	44%	32%	62%

Negative results for software effort Estimation, **Empirical Software Engineering**, Nov 2016
Menzies, Yang, Mathew, Boehm, Hihn

Model MRE Performance

Model Estimation Error, based on MRE, is steadily improving

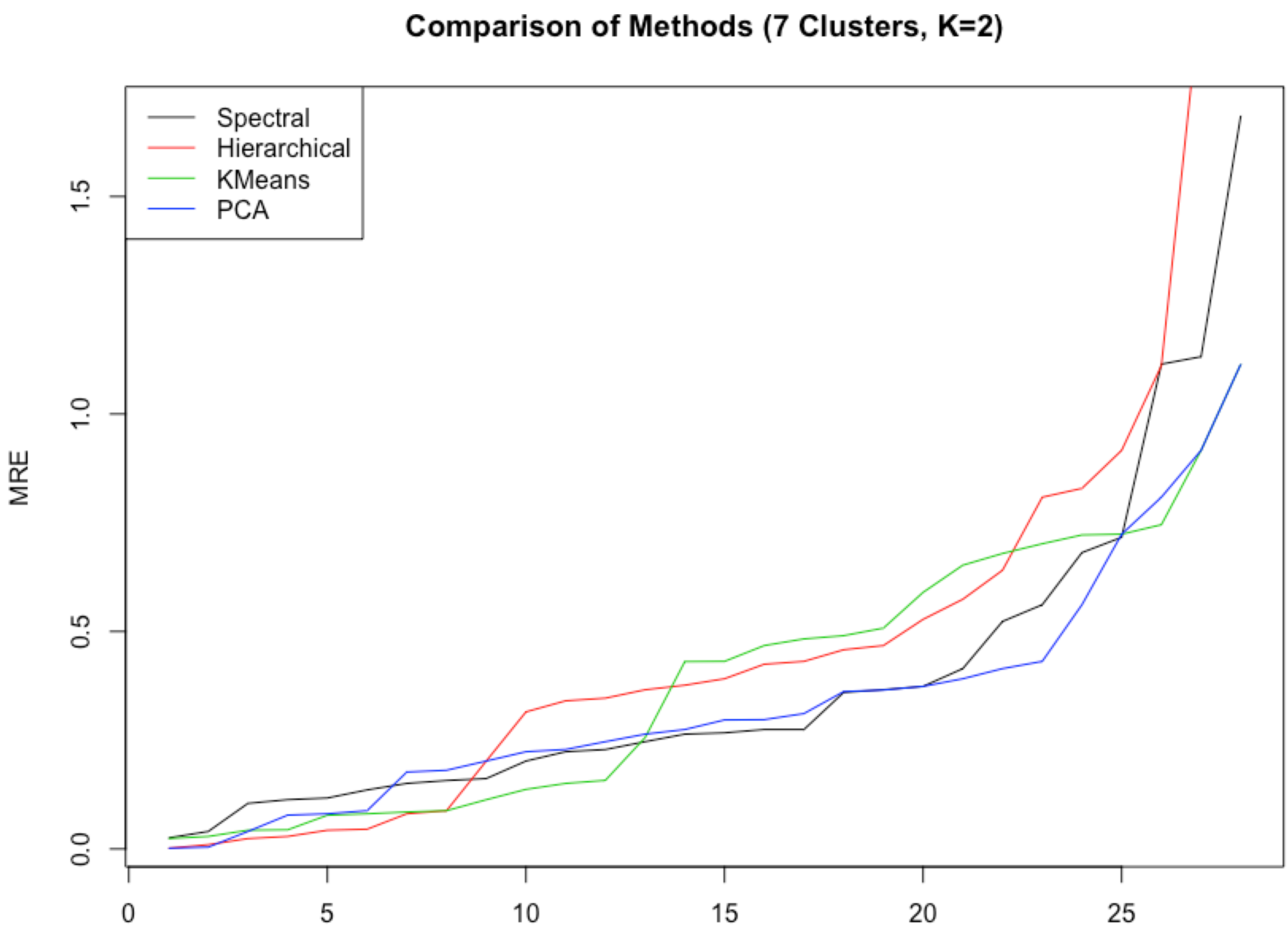


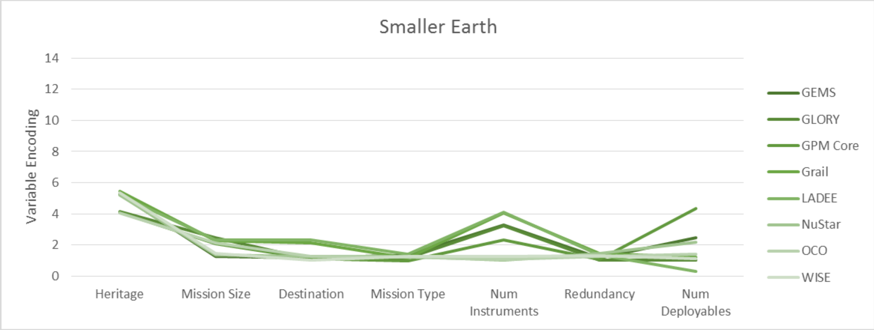
MRE Comparison Based on Test Cases

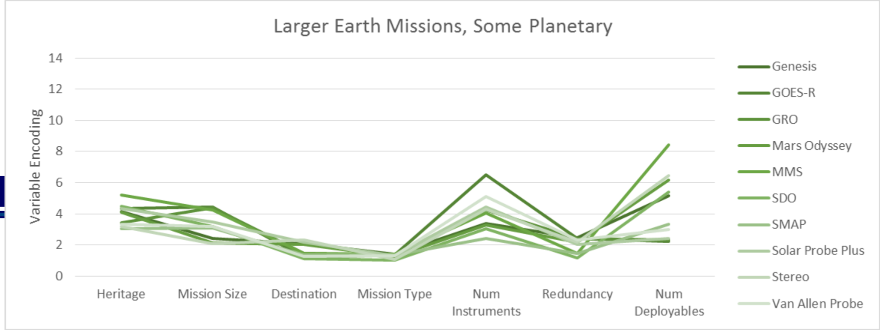
	ASCoT Prototype	ASCoT Beta	ASCoT
1	0%	1%	2%
2	1%	3%	3%
3	3%	3%	7%
4	4%	10%	8%
5	4%	22%	15%
6	35%	23%	27%
7	45%	29%	32%
8	79%	35%	35%
9	101%	37%	37%
10	102%	51%	51%
11	192%	54%	54%
12	506%	175%	107%
Median MRE	40%	26%	30%
Average MRE	89%	37%	32%

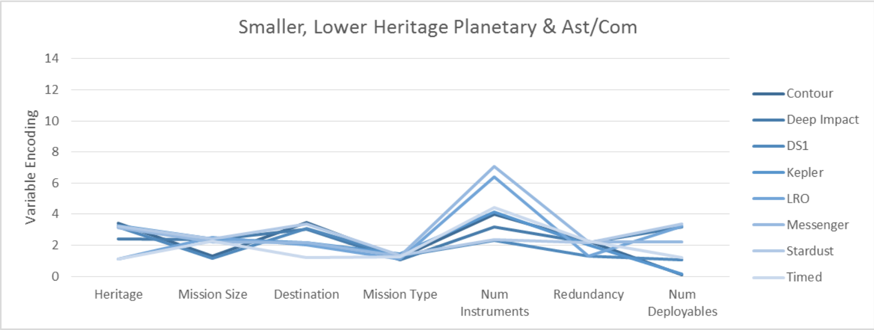
Inner Quartile

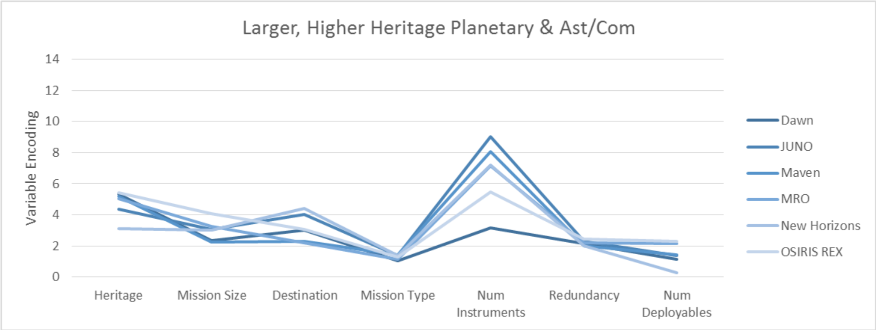
For PCA Pred (50) = 86%

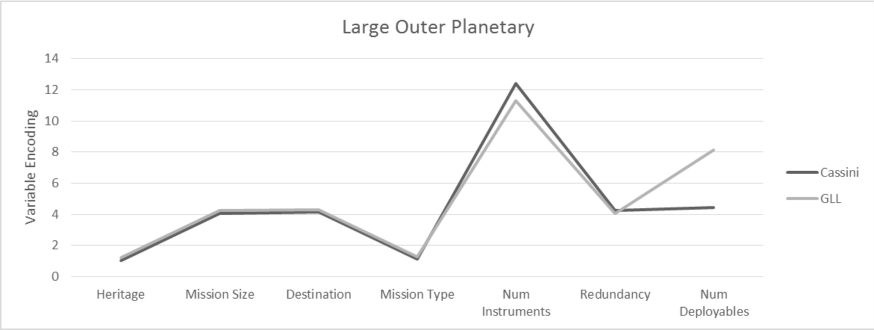


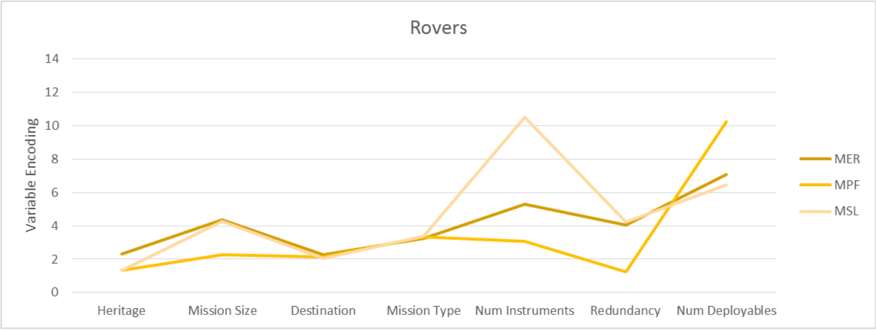




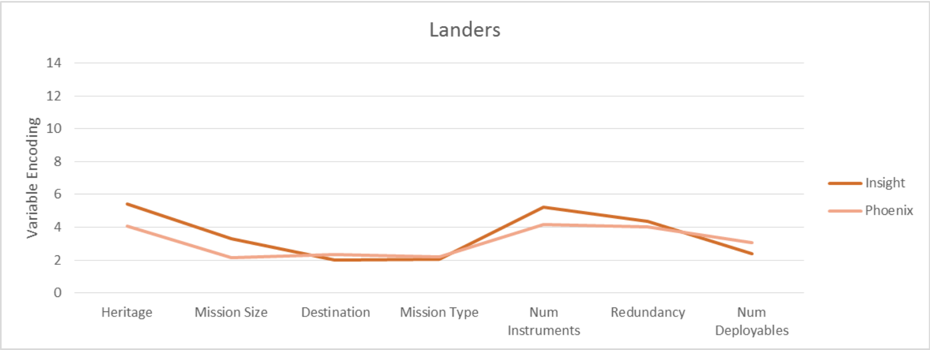






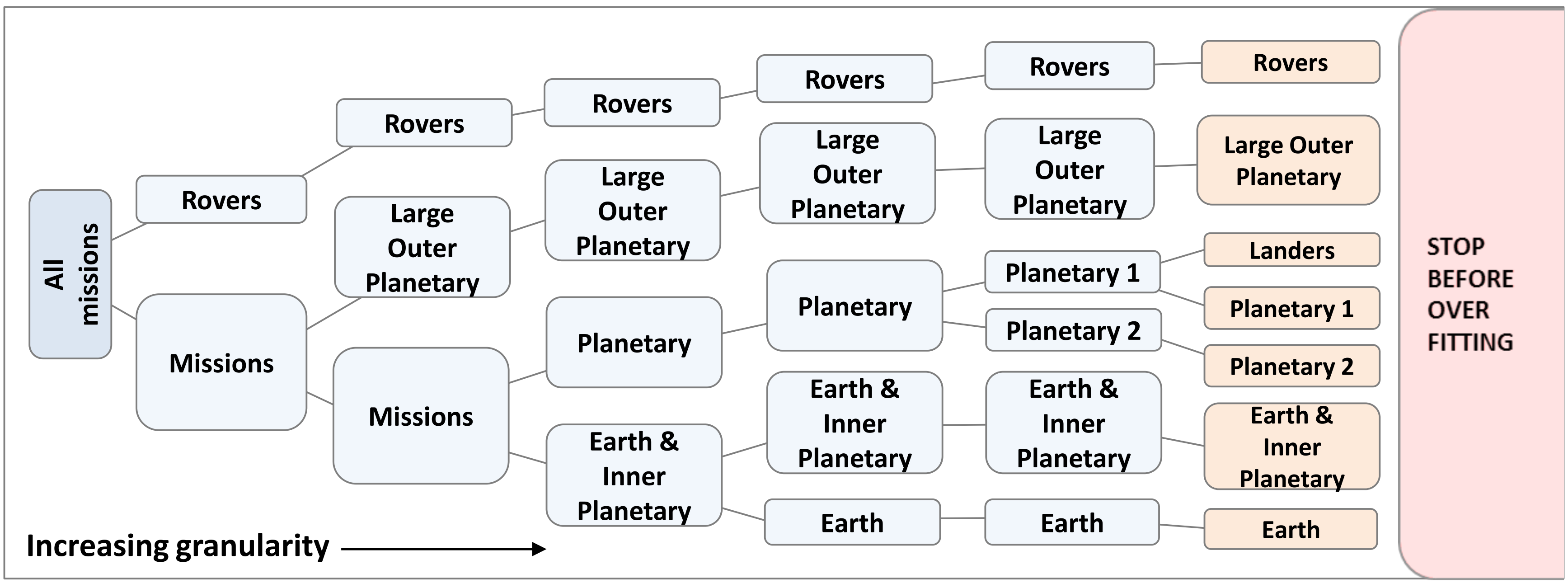


Cluster Parameter Variation



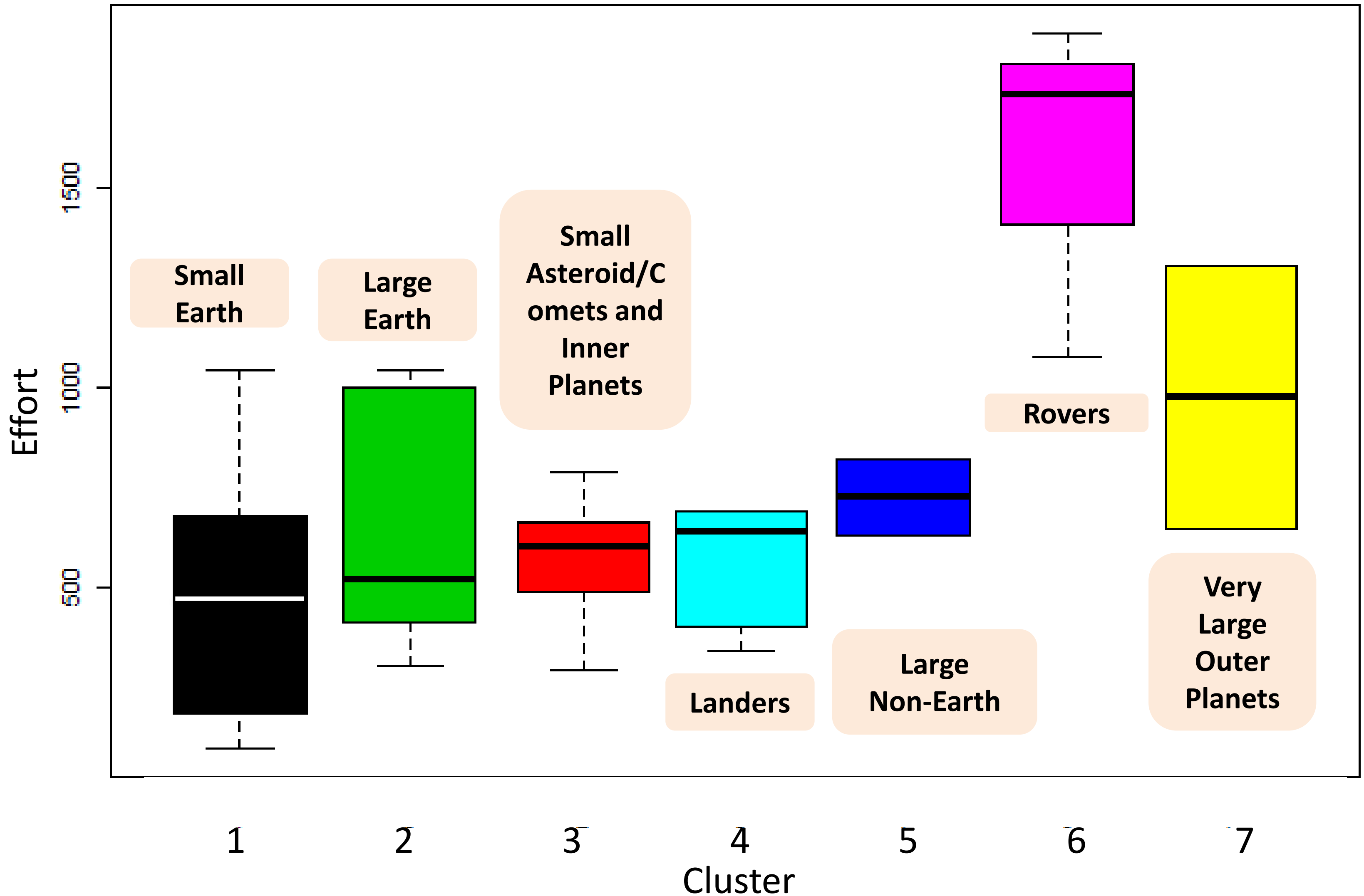
Clustering Analysis 2

By gradually increasing the granularity of our clusters, while maintaining robustness to avoid overfitting, we were able to find logical separation between groupings of missions



Number of Clusters	2	3	4	5	6	7	8

Reduced Cluster Effort Variation



Cluster Parameter Summary

Cluster	Mission Cost Median	Mission Cost Range	Software Inheritance	Destination	Mission Type	flight Computer Redundancy	Number of Instruments	Number of Deployabes	Development Work Months Median	Development Work Months Range
1	$321M	$170M – $500M	High-Very High	Earth	Orbiter	Single String	1 to 4	0 to 4	492	230 to 870
2	$824M	$420M – $1,250M	Medium to High	Earth & Inner Planets	Orbter	Dual String – Cold backup	2 to 6	2 to 8	603	340 to 790
3	$292M	$220M – $550M	Medium	Asteroid/Comets & Inner Planets	Orbiter/ Flyby	Dual String – Cold backup	2 to 7	0 to 3	525	450 to 1040
4	$548M	$630M – $820M	High-Very High	Inner Planet (Mars)	Lander	Dual String – Warm backup	4 to 5	2 to 3	728	630 to 820
5	$696M	$550M – $850M	High-Very High	Planets & Asteroids/Comet	Orbiter/ Flyby	Dual String – Cold backup	3 to 9	0 to 3	641	400 to 690
6	$1,123M	$420M – $2,600M	None-Low	Inner Planet (Mars)	Rover	Dual String – Warm backup	3 to 10	6 to 10	1735	1000 to 1890
7	$2680M	$2,300M – $3,000M	None-Low	Outer Planets	Orbiter/ Flyby	Dual String – Warm backup	11 to 12	4 to 8	978	650 to 1300

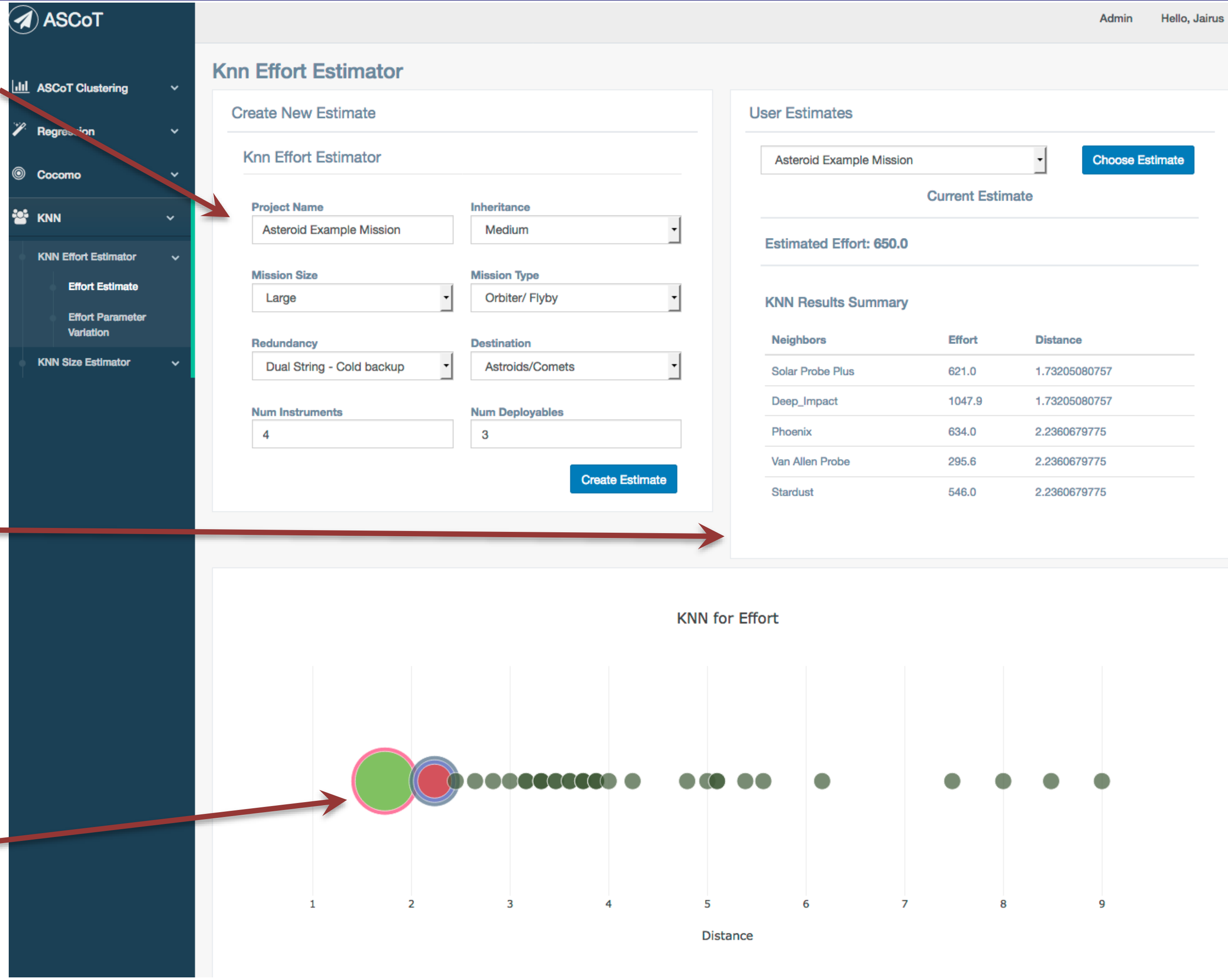
The cost information contained in this document is of a budgetary and planning nature and is intended for informational purposes only. It does not constitute a commitment on the part of JPL and/or Caltech

ASCoT Web Model:
KNN Model Main View

Model Inputs

Estimate

Results based on Euclidian distance



Conclusions

- Our research has demonstrated that for a well defined domain that cluster based algorithms can predict software development costs within +/- 50% using a small number of system level categorical parameters.

ASCoT Publications & Presentations

Publications: Conference

2. IEEE Aerospace
   - Improving and Expanding NASA Software Estimation Methods, 2016 Aerospace Conference, Big Sky, Mt., March 2016.
   - NASA Analogy Software Cost Model: A Web-Based Cost Analysis Tool, , 2017 Aerospace Conference, Big Sky, Mt., March 2017.

2. Automation in Software Engineering (ASE)
   - Data Mining Methods and Cost Estimation Models: Why is it so hard to infuse new ideas? , Automation in Software Engineering 2015, Norman, Nebraska, Nov. 2015.

1. International Cost Estimation and Analysis Association (ICEAA)
   - NASA Software Cost Estimation Model: An Analogy Based Estimation Method, 2015 International Cost Estimation and Analysis Association (ICEAA) Professional Development & Training Workshop, San Diego California, June 2015
   - A Next Generation Software Cost Model, 2014 International Cost Estimation and Analysis Association (ICEAA) Professional Development & Training Workshop, Denver Colorado , June 2014.

Publications: Journal

1. **Empirical Software Engineering**
   - Negative results for software effort Estimation, Empirical Software Engineering, Nov 2016. Menzies, Yang, Mathew, Boehm, Hihn

1. NASA Cost Symposium
   - ASCoT R2: A web-based model of the NASA Analogy Software Costing Tool, Goodbye Excel", 2016 NASA Cost Symposium, NASA Glen Research Center, August. 2016. J. Hihn and J. Johnson
   - NASA Software Cost Estimation Model: An Analogy Based Estimation Method. 2015 NASA Cost Symposium, NASA Ames Research Center, August 2015. J. Hihn and J. Johnson.
   - A Next Generation Software Cost Model: A look under the Hood. 2014 NASA Cost Symposium, NASA Langley Research Center, August 2014. J. Hihn and J. Johnson.

2. COCOMO Workshop
   - NASA Analogy Software Costing Tool-ASCoT, 31tst International Forum on COCOMO and System/Software Cost Modeling,USC, October 2016. J. Hihn & M. Saing
   - Just How Good is COCOMO and Parametric Estimation?, , 29th International Forum on COCOMO and System/Software Cost Modeling, USC, October 2014. Hihn et al.

Effort Estimation with Data Mining Methods References

"Active Learning and Effort Estimation: Finding the Essential Content of Software Effort Estimation Data" by Ekrem Kocaguneli and Tim~Menzies and Jacky Keung and David Cok and Ray Madachy. IEEE Transactions on Software Engineering (pre-print) 2013 . .

"Finding conclusion stability for selecting the best effort predictor in software effort estimation" by J. Keung and E. Kocaguneli and T. Menzies. Automated Software Engineering pages 1-25 May 2012 . Available from http://menzies.us/pdf/12findstable.pdf .

"Exploiting the Essential Assumptions of Analogy-Based Effort Estimation" by E. Kocaguneli and T. Menzies and A. Bener and J. Keung. IEEE Transactions on Software Engineering pages 425-438 2012 . Available from http://menzies.us/pdf/11teak.pdf .

"Local vs. Global Lessons for Defect Prediction and Effort Estimation" by Menzies, T. and Butcher, A. and Cok, D. and Marcus, A. and Layman, L. and Shull, F. and Turhan, B. and Zimmermann, T.. IEEE Transactions on Software Engineering pages 1 2012 . Available from http://menzies.us/pdf/12localb.pdf .

"Kernel methods for software effort estimation" by E. Kocaguneli and T. Menzies and J. Keung. Empirical Software Engineering pages 1-24 2011

"On the Value of Ensemble Effort Estimation" by Kocaguneli, E. and Menzies, T. and Keung, J.. IEEE Transactions on Software Engineering 2011

"Exploring the Effort of General Software Project Activities with Data Mining" by Topi Haapio and Tim Menzies. International Journal of Software Engineering and Knowledge Engineering pages 725-753 2011

"Stable Rankings for Different Effort Models" by Tim Menzies and Omid Jalali and Jairus Hihn and Dan Baker and Karen Lum. Automated Software Engineering December 2010 . Available from http://menzies.us/pdf/10stable.pdf .

"Case-Based Reasoning for Reducing Software Development Effort" by Adam Brady and Tim Menzies and Oussama El-Rawas and Ekrem Kocaguneli and Jacky Keung. Journal of Software Engineering and Applications 2010 . Available from http://menzies.us/pdf/10w0.pdf .

"A Second Look at Faster, Better, Cheaper" by Oussama El-Rawas and Tim Menzies. Innovations Systems and Software Engineering pages 319-335 2010 . Available from http://menzies.us/pdf/10bfc.pdf .

"Explanation vs Performance in Data Mining: A Case Study with Predicting Runaway Projects" by Tim Menzies and O. Mizuno and Y. Takagi and Y. Kikuno. Journal of Software Engineering and Applications pages 221-236 November 2009

"Accurate Estimates Without Local Data?" by Tim Menzies and S. Williams and Oussama El-Rawas and D. Baker and B. Boehm and J. Hihn and K. Lum and R. Madachy. Software Process Improvement and Practice pages 213-225 July 2009 . Available from http://menzies.us/pdf/09nodata.pdf .

"Selecting Best Practices for Effort Estimation" by Menzies, Tim and Chen, Zhihao and Hihn, Jairus and Lum, Karen. IEEE Transactions on Software Engineering pages 883--895 doi = 10.1109/TSE.2006.114 issue = 11 2006

Acknowledgements

- Many individuals have contributed or assisted with this work:
  - JHU APL: Nicole Powers-Krepps, Sally Whitley, Meagan Hahn, Christian Patton
  - NASA GRC: Elizabeth (Betsy) Turnbull, Chris Blake, Tom Parkey, Bob Sefcik
  - NASA HQ: Cris Guidi, Charley Hunt, Doug Comstock, Eric Plumer
  - NASA GSFC: Stephen Shinn, Tamra Goldstein
  - NASA ARC: Tommy Paine
  - Special thanks to Julie McAffee and Mike Blandford of ONCE team